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Scoring functions and bankruptcy prediction models – case study for Romanian companies

Cimpoeru Smaranda^{a*}^a*Department of Statistics and Econometrics, Bucharest University of Economic Studies, nr. 6 Romana Square, 010374 Bucharest, Romania*

Abstract

The purpose of our study is to test the performance bankruptcy prediction models in the recent financial crisis context. We will refer to classic score models, like Altman or Taffler and also logistic regression methods. We apply them on a sample of SME data collected from a central-east European emerging economy, at the end of 2009. The results are in line with the literature – in a financial crisis context, the classical models have to be re-estimated and the financial ratios reconsidered.

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1. Importance of credit risk measurement and basic principles for credit risk assessment

Credit risk has been in the attention of researchers and bankers for decades, as a field of continuous sources for modelling, inter-disciplinary processes and estimation techniques, statistical and econometrical methods. As a general definition, we can say that the credit risk is the risk associated with the unexpected changed in the quality of the debtor. The measurement of this risk is one of the major challenges of modern economic and financial research.

Credit risk measurement has grown into a new dimension of increased importance in the new context of global financial crisis which arose from 2007. It is a known fact that most of the existing credit risk assessment models have failed in predicting the default cases recorded in global crisis situation. In January 2009, New York Times stated: “The best Wall Street minds and their best risk-management tools failed to see the crash coming”. There are many studies related to this subject, the causes which lead to the failure of the risk models in crisis situation. Jorion,

* Corresponding author. Tel.: +40 721 67 55 85;

E-mail address: smarandacimpoeru@yahoo.com.

P. (2009), notes that the losses arose from the 2007 crisis are without precedent. The losses estimated by the International Monetary Fund on US assets are of over \$4.000 billion. In his paper, Jorion concludes that risk management systems have to be improved with a greater emphasis on stress tests and scenario analysis.

Crouhy mentions that the major weaknesses in risk assessment and risk modeling come from an “over-reliance on: misleading ratings from rating agencies; unrealistically simple risk models, i.e., models that were not designed to deal with the complexity of structured credit products; inaccurate data; short-term financing with too little consideration for liquidity risk”.

1.1. Credit risk evolution in the context of the global financial crisis

The financial crisis that started in 2008 is considered to have as one of its triggers the lack of systemic risks from the housing market that should have been taken into account in the macroeconomic policies. By many analysts, the main cause for the housing bubble in US is the low interest rate policy promoted by the Federal Reserve. This comes as a consequence of the small margins obtained by the banks that were countered by an increased volume in loans. Due to the pressure of granting more loans, the process of crediting became speculative and risk management was overlooked.

Serrano-Cinca et al. (2011) formulate four hypothesis for the failure of a bank. First of all, they note that there are financial symptoms preceding failure, main symptoms in banking industry being the lack of profit, low solvency and drops in efficiency and financial ratios stability. The second hypothesis formulated deals with the risks of specialization in a bank. Although specialized banks could be associated with higher profits and profit efficiency, the risk of concentration is very important, especially if the concentration is on real-estate credits, considering the collapse that happened with the real estate sector in the US housing market.

The third hypothesis approaches the loan growth. More precisely, they draw attention to “rash of troubled loans”, that could lead to bankruptcy. This was also proved by a historical study of De Roover (1963) – he concluded that the failure the fourteenth century Florentine Banks was most probably caused by a too broad extension of credit. In the end, Serrano-Cinca et. al (2011) conclude about the two different strategies that could be approached by a bank: increased volumes or increased profitability, each of them can be successful depending on the market conditions.

There is a tendency of building credit risk management system with more automated techniques for the small exposures (classified by the Basel agreements as retail class of assets), but a judgmental analysis for non-retail exposures, as stated by the Basel principles. The threshold for clustering the two types of asset classes (retail and non-retail) has not been clearly stated by the Basel specialists, letting each bank decide this threshold as a function of the each bank characteristics and macroeconomic context.

The Basel II principles encourage banks to adopt internal rating based models in order to calculate risk weight assets. The basic idea of an internal rating model developed by a banking institution is the increased sensitivity to the risky elements that influence the quality of assets, which means an increased attention to the potential losses in a credit portfolio. Thus, the banks are obliged to assess the probability of default for each debtor in a portfolio.

The Basel II regulatory frame which became mandatory since January 2007, created conceptual, strategic and methodology controversies. A “best practices” set was needed to permit the unification of the regulatory approached bank wide. The key variables in the credit risk portfolio models are three parameters: probability of default, loss given default, exposure at default. The correct and accurate estimation of the three parameters is essential for management and an efficient measurement of the credit risk.

Out of the three parameters, the estimation of the default probability offers the possibility of utilizing the most diversified range of methods and statistic techniques. The assessment of the default probability is a fundamental aspect in credit risk management, important both for creditors and debtors. On one side, the creditors are interested in the quality of their portfolio of clients in order to minimize the risk/profit ratio. On the other side, the debtors are interested to be evaluated by the rating agencies with the purpose of obtaining a better price for financing. The estimation of the default probability is the core element of the rating models.

1.2. Structure

In the first part of the paper, we review the scoring techniques and the findings from the specialty literature. In the following section, we present the statistical notions that we apply in the remaining of the paper. In the case study, we try to estimate multiple scoring models in order to determine the best one to be used on a set of Romanian companies.

2. Scoring techniques – review from the literature

Scoring techniques applied for companies are also called bankruptcy models. There are multiple statistic methods that stand behind the scoring functions. Firstly, there are the parametric methods: multiple discriminant analysis (pioneered by Beaver, 1966; Altman, 1968), logit and probit regression (Ohlson, 1980) or survival models (Narain, 1992). Secondly, at the beginning of the 90's, the neural calculus is used in the assessment of credit risk. Neural networks are applied for the first in the assessment of SMEs credit risk by Wu, Wang (2000), while self-organizing maps are used by Serrano-Cinca (1996); recent machine learning techniques used in credit risk are: fuzzy adaptive networks (Jiao et al., 2007) and support vector machines (Huang, 2004; Kim, Sohn – first study of support vector machines on SMEs in 2010). A more wide survey of the literature can be found in Boritz et al. (2007).

2.1. Traditional scoring techniques

However, the majority of the failure prediction studies and financial institutions employ the multiple discriminant analysis or the logistic regression, as seen from the literature review. This can be explained especially by the ease of the computational method, as well as by the possibility of formulating classification rules for the evaluated groups of companies, whereas the black-box system of the second class of models mentioned above does not permit the visualization of the decision rule behind the technique. This makes the results difficult to interpret and is the main disadvantage of these methods. In this way, we argue our choice for exploring in our analysis only the MDA (multiple discriminant analysis) and logistic regression techniques.

In what follows we make a brief review of the MDA techniques. Beaver (1966) was the first to use univariate discriminant analysis and found that the cash flow/total debt ratio gave statistically significant signals before actual default of the company. In 1968, Altman extended Beaver's study, in "a single measure of a number of appropriately chosen financial ratios, weighted and added" (Agarwal, Taffler, 2007). The measure is called Z-Score and is very widely used even nowadays.

The Z-score, or the multiple discriminant function is a linear combination of five financial ratios:

$$Z = 1,2 * T1 + 1,4 * T2 + 3,3 * T3 + 0,6 * T4 + 0,995 * T5$$

where: $T1 = \text{Working Capital} / \text{Total Assets}$; $T2 = \text{Retained Earnings} / \text{Total Assets}$; $T3 = \text{Earnings Before Interest and Taxes} / \text{Total Assets}$; $T4 = \text{Market Value of Equity} / \text{Total Liabilities}$; $T5 = \text{Total Sales} / \text{Total Assets}$.

Companies with a calculated Z-score less than 2.675 are included in the default firms group, while the ones with a score greater than the cut-off value 2.675 are considered non-defaulted or "good" debtors.

The Z-score model was the first MDA function built and it has multiple variations. The most known is Taffler score (1983). The Taffler function for fully listed industrial firms is the following:

$$ZT = 3.2 + 12.18 * X1 + 2.5 * X2 - 10.68 * X3 + 0.029 * X4$$

Where: $X1 = \text{profit before tax} / \text{current liabilities}$; $X2 = \text{current assets} / \text{total liabilities}$; $X3 = \text{current liabilities} / \text{total assets}$; $X4 = (\text{quick assets} - \text{current liabilities}) / \text{daily operating expenses with the denominator proxied by } (\text{sales} - \text{profit before taxes} - \text{depreciation}) / 365$.

The relative contributions of each financial ratio to the overall discriminant power of the model are as follows: 53% for $X1$, 13% for $X2$, 18% for $X3$ and 16% for $X4$ (measured with the Mosteller-Wallace criterion). The four ratios chosen (identified by factor analysis) correspond to the firm's financial profile: profitability, working capital

position, financial risk and liquidity. For this model, the solvency threshold is zero. That is, “if the computed Z-score is positive (...), the firm is solvent and is very unlikely indeed to fail within the next year. However, if the underlying Z-Score is negative, it lies in the ‘at risk’ region and the firm has a financial profile similar to previously failed business (Agarwal, Taffler, 2007). The Taffler score was developed on UK data. In 2007, Taffler evaluates the score’s performance and its prediction ability over the 25-year period since it was originally developed. He argues that “(...) z-score models, if carefully developed and tested, continue to have significant value for financial statement users concerned about corporate creditrisk and firm financial health. They also demonstrate the predictive ability of the underlying financial ratios when corectly read in a holistic way.” (Agarwal, Taffler, 2007).

2.2. Recent developments in scoring techniques

The logit regression was first applied by Ohlson (1980), as a means of incorporating conditional probabilities into financial distress models. Ohlson used nine financial ratios combined in the following equation, in order to assess the probability of bankruptcy:

$$OS = -1.33 - 0.407 * X1 + 6.03 * X2 - 1.43 * X3 + 0.076 * X4 - 2.37 * X5 - 1.83 * X6 + 0.285 * X7 - 1.72 * X8 - 0.521 * X9$$

Where: $X1 = \ln(\text{total assets}/\text{GNP price level})$; $X2 = \text{total liabilities}/\text{total assets}$;

$X3 = \text{Working capital} / \text{total assets}$; $X4 = \text{current liabilities}/\text{current assets}$;

$X5 = \text{net income} / \text{total assets}$; $X6 = \text{operational cash-flow} / \text{total liabilities}$;

$X7 = 1$ if Net Income was negative for the last two years and 0 otherwise;

$X8 = 1$ if total liabilities > total assets and 0 otherwise;

$X9 = (NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where $NI = \text{Net Income}$.

The cut-off value of Ohlson Score is 0.038. We note an important difference versus the MDA analysis – the score obtained by applying the logistic regression can be interpreted as an insolvency probability, while a score calculated with MDA techniques cannot be interpreted as it is. The threshold value of 0.038 means that the companies with a calculated O-Score above 0.038, thus with a probability of default greater than 38%, will be included in the defaulted group of firms.

Recent MDA models are that of Boritz et al. (2007) who re-estimated the Z-score using Canadian company data. They obtained the following score function:

$$ZB = 2.149 * X1 - 0.624 * x2 + 1.354 * X3 - 0.018 * X4 + 0.463 * X5$$

The ratios are the same as in the Z-score model, thus their aim is to re-estimate the coefficients of the Altman model on Canadian data. They argue that the original samples used by Altman and Ohlson are 30 to 60 years old and for a restricted set of industries. “The suitability and performance of these models in the new millennium is an empirical question because there have been many changes in business conditions since these models were re-estimated. For example, there have been changes to business practices, such as increased tolerance of debt financing, changes to bankruptcy laws, and varying economic cycles” (Boritz et al., 2007). Their results indicate that the Ohlson model yields better performance than other models and is robust over time. Also, they find all models have stronger performance with the original coefficients than with the re-estimated coefficients. This is an argument for the generality of the Altman and Ohlson models.

Also, as more recent score models, we mention the one applied to Latin America emergent economy data (Argentina), developed by Sandin and Porporato (2007). Using a stepwise selection, they retain 2 out of 13 ratios: operative income/net sales and shareholder’s equity/total assets. For China publicly listed companies, Wang and Campbell (2010) developed a re-estimated model for which the coefficients in Altman’s score were recalculated and a revised model which used different models. They found that the re-estimated model had higher prediction accuracy for predicting non-defaulted companies, whereas Altman’s score proved a higher accuracy for predicting defaulted firms. The revised Z-score model had higher accuracy compared with both re-estimated and original

Altman models. They conclude that the Z-score model is a helpful tool in predicting failure of a publicly listed firm in China.

3. Statistical methods in accounting based rating models

The two most known techniques in this type of rating models are the discriminant analysis and the logistic regression. We briefly introduce the discriminant analysis, while we offer more attention to the logistic regression method.

Discriminant analysis is the technique used to test the equality between the means of two or more groups of objects. In order to test this hypothesis, the discriminant analysis multiplies each independent variable to the respective weight and sums up these products resulting in the discriminant score, calculated for each object in the selected sample.

By calculating the average over all the scores for the individuals in a certain group we obtain the group mean, also called the centroid. The number of centroids in the analysis equals the number of classification groups. The test for the statistical significance of the discriminant function is a generalized measure for the distance between the groups' centroids.

In what follows, we will review, in more detail, the logistic regression technique. We choose to present this method as in the literature it has been proven to give the best results. In the logistic regression context, the supplementary restriction considers that the dependent variable, Y , takes only two values. To overcome this restriction, the most known approach is that of a latent variable defined as follows:

$$y_i^* = \beta_0 + \sum_{j=1}^k \beta_j x_{ij} + u_i$$

The latent variable, y_i^* is not observable. The variable which we observe is y_i which we define:

$$y_i = \begin{cases} 1, & \text{if } y_i^* > 0 \\ 0, & \text{if } y_i^* \leq 0 \end{cases}$$

From the definition of y_i , if we multiply y_i^* with any positive constant, the observed variable doesn't change, meaning that we can estimate β up to a positive multiplier. That is why, we usually consider $\text{var}(u_i) = 1$.

We have:

$$\begin{aligned} P_i = \text{Prob}(y_i = 1) &= \text{Prob}\left(\beta_0 + \sum_{j=1}^k \beta_j x_{ij} + u_i > 0\right) = \text{Prob}[u_i > -(\beta_0 + \sum_{j=1}^k \beta_j x_{ij})] = 1 - \text{Prob}[u_i \\ &\leq -(\beta_0 + \sum_{j=1}^k \beta_j x_{ij})] = 1 - F(-(\beta_0 + \sum_{j=1}^k \beta_j x_{ij})) \end{aligned}$$

where F is the cumulative distribution function for u . Moreover, if u 's distribution is symmetric, we will have:

$$P_i = \text{Prob}(y_i = 1) = 1 - F(-(\beta_0 + \sum_{j=1}^k \beta_j x_{ij})) = F(\beta_0 + \sum_{j=1}^k \beta_j x_{ij}) \quad (1)$$

What we have written above represent the probability distribution for y_i . The maximum likelihood function is:

$$L = \prod_{y_i=1} P_i \prod_{y_i=0} (1 - P_i) \quad (2)$$

The distribution of the error term, u , gives the function F and the model type. Two functions are the most known in practice:

- The cumulative distribution function of u is logistic, giving the logit model:

$$F(z) = \frac{e^z}{1 + e^z} \Rightarrow F(z) + F(z) \cdot e^z = e^z \Rightarrow e^z = \frac{F(z)}{1 - F(z)} \Rightarrow z = \log\left(\frac{F(z)}{1 - F(z)}\right)$$

thus, if we use the result above in the relation (1), we will have:

$$\log \frac{P_i}{1 - P_i} = \beta_0 + \sum_{j=1}^k \beta_j x_{ij}$$

- The cumulative distribution function of u is normal, giving the probit model:

$$F(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$$

or:

$$P_i = \Phi(\beta_0 + \sum_{j=1}^k \beta_j x_{ij})$$

The maximization of L in (2) is made with standard procedures, in the scope of finding the estimations for the coefficient vector, β . L can be written as:

$$L = \prod_i \{y_i \ln F(\beta'x) + (1 - y_i) \ln [1 - F(\beta'x)]\}$$

With the first order conditions:

$$\frac{\partial \ln L}{\partial \beta} = \sum_i [y_i \frac{f_i}{F(\beta'x_i)} + (1 - y_i) \frac{-f_i}{1 - F(\beta'x_i)}] x_i = 0$$

The number of equations of this type equals the number of exogenous variables of the model. The equations are not linear, having iterative solution. The first order condition resemble the orthogonality conditions between the residuals and the explicative variables in a standard regression model. In the logit model, the residual are given by:

$$\hat{u}_i = y_i - \frac{e^{\hat{z}_i}}{1 + e^{\hat{z}_i}}, \quad \text{and } \hat{z}_i = \hat{\beta}_0 + \sum_{j=1}^k \hat{\beta}_j x_{ij}$$

The residuals measure the distance between the observed variable, y_i and the value estimated in the model – thus the distance between the estimated model and the real situation.

4. Case study

In the case study, we propose a comparison between three “hybrid” rating models, constructed only on accounting ratios. The three models we construct are: the classic Altman score, the Taffler score and a logistic score for which we will choose the financial ratios after conducting a cluster analysis. The scope of the analysis is to determine the technique with the highest discriminatory power.

The common sample for the three rating models is a set of financial data collected from 105 small companies in Romania, with a turnover between EUR 700.000 and EUR 3.755.000 at the end of 2009. 75 of the entities in the sample are non-defaulted companies and 30 are defaulted cases. A firm is considered defaulted if the insolvency procedure was started in 2010. Data are collected from the financial statement at the end of 2009 (public available data). So, the default is observed in the next 12 months from the ending of the input data observation period. The chosen sample represents about 2% of the total population of companies with the turnover in the mentioned interval.

Firstly, we compute the Z-Score, introduced by Altman, as seen in a previous section of the paper. By calculating the Z-score for the 105 entities in our sample, we obtain a range of scores from -2.83 to 16.12. We apply the same threshold used by Altman, that is: if the value of the Z score is above 2.99, than the company is placed in the “Safe Zone”, if the score ranges between 1.81 and 2.99, the company is considered to be in the “Grey Zone” and if the Z score is lower than 1.81 than the company is included in the “Distress” Zone, meaning it will most likely that the respective firm will become bankrupt in the next 12 months. Based on these thresholds we get the following classification:

Table 1 – Classification table based on the Altman score

Actual classification	Altman Score		Total
	Non Distress	Distress	
Non-Default	38	37	75
Default	5	25	30
Total	43	62	105

We found that 83% of companies are correctly classified in the bankrupt category one year before the event, but the Type II Error (classifying the firm as bankrupt when it does not default) is 49%, that is almost as a random model.

Next, we compute the Taffler score. The calculated values range from -9.57 to 9.07. As noted earlier, for this score we have a zero threshold. That is, if a company has a calculated Taffler score below zero, it can be considered to become bankrupt in one year time period. Based on this, we obtain the following classification:

Table 2 – Classification table based on the Taffler score

Actual classification	Taffler Score		Total
	Non-Bankruptcy	Bankruptcy	
Non-Default	32	43	75
Default	1	29	30
Total	33	72	105

Although the accuracy ratio is very good, over 90%, we cannot ignore the Type II Error which stands at a very high 57% - this suggests a possible reconsideration of the threshold. After multiple simulations, we obtain that an optimal value for the threshold to separate between the two categories as -3. If a company has a calculated score of below -3, then it is included in the “one-year default” category. The new classification based on the reconsidered threshold value is as follows:

Table 3 – Classification table based on the Taffler score (reconsidered threshold)

Actual Classification	Taffler Score (modified threshold)		Total
	Bankruptcy	Non-Bankruptcy	
Non-Default	52	23	75
Default	5	25	30
Total	57	48	105

We obtain a considerably improved Type II Error of 30%, whereas the accuracy ratio decreases to 83%. The results are better than the ones obtained from the Altman score, considering both the accuracy and the level of the type II error.

In the third place, we estimate our own scoring function. For this, we must first choose the accounting ratios to be used in the model. Our choice of financial ratios is based on the set of ratios usually used in the literature combined with data availability. The initial set of financial ratios is listed in the table below.

Table 4 – The initial set of accounting ratios

Number	Accounting Ratio
R1	Debt to Equity
R2	Return on Assests
R3	Return on Equity
R4	Receivables Rotation
R5	Sales on Total Assets
R6	Sales to Equity
R7	Debt to Assets
R8	Stock to Total Assets
R9	Working Capital / Total Assets
R10	Retained Earnings / Total Assets
R11	Earnings before interest and taxes / Total Assets
R12	Equity / Total Liabilities
R13	Current liabilities / Current Assets
R14	Return / Sales

In order to depict the most relevant ratios, we first conduct a factor analysis on the set of ratios. We decide to settle with five clusters. These are depicted in the table below:

Total variation explained = 9,945827 Proportion = 0,7104

5 Clusters		R-squared with			Variable Label Label
Cluster	Variable	Own Cluster	Next Closest	1-R**2 Ratio Ratio	
Cluster 1	R2	0,6659	0,1280	0,3832	R2
	R9	0,6326	0,3184	0,5391	R9
	R10	0,6659	0,1280	0,3832	R10
	R11	0,7639	0,3245	0,3496	R11
	R12	0,2024	0,1239	0,9104	R12
	R14	0,5030	0,4253	0,8648	R14
Cluster 2	R1	0,8060	0,0088	0,1957	R1
	R3	0,6889	0,2321	0,4052	R3
	R6	0,8843	0,2611	0,1566	R6
Cluster 3	R5	1,0000	0,1050	0,0000	R5
	R13	1,0000	0,1050	0,0000	R13
Cluster 4	R4	0,6285	0,0763	0,4022	R4
	R7	0,6285	0,5349	0,7988	R7
Cluster 5	R8	1,0000	0,0012	0,0000	R8

Figure 1 – Factor analysis on the set of 14 ratios (SAS output table)

We retain only one ratio from each cluster: R10 from the first cluster, R1 from the second one, R5 from the third, R7 from the fourth and R8, the only ratio in the last cluster. Thus, we have limited the analysis to five ratios: R1, R5, R7, R8, R10.

For the consistency of the analysis, we will conduct a correlation analysis. We calculate the Spearman correlation coefficients between each two ratios (table 6). We cannot reject the null hypothesis for the correlation coefficient in three cases (when the calculated probability associated with the null hypothesis is less than 10% or

0.1): R10 and R5 – with a calculated correlation coefficient of 0.436; R10 and R7 – with a calculated correlation coefficient of 0.453; R1 and R7 – 0.346. We consider for elimination only the ratio R10, as the value of the calculate correlation coefficient between R1 and R7 is less than 0.4. Thus we have a remaining set of four ratios: R1, R5, R7 and R8.

Simple Statistics							
Variable	N	Mean	Std Dev	Median	Minimum	Maximum	Label
R1	105	8.55811	42.43681	2.94666	-76.65754	402.44240	R1
R10	105	0.05123	0.08731	0.00795	0	0.47568	R10
R7	105	0.76852	0.39019	0.73818	0.03740	2.24070	R7
R8	105	31.04632	61.14474	8.10452	0	383.07658	R8
R5	105	2.37999	7.74515	1.28898	0.23894	79.76042	R5

Spearman Correlation Coefficients, N = 105
Prob > |r| under H0: Rho=0

	R1	R10	R7	R8	R5
R1	1.00000	0.05181	0.34606	-0.11744	-0.04876
R1		0.5997	0.0003	0.2328	0.6214
R10	0.05181	1.00000	-0.45336	-0.03525	0.43663
R10		0.5997	<.0001	0.7211	<.0001
R7	0.34606	-0.45336	1.00000	-0.11059	-0.03167
R7		0.0003	<.0001	0.2614	0.7484
R8	-0.11744	-0.03525	-0.11059	1.00000	0.10256
R8		0.2328	0.2614		0.2978
R5	-0.04876	0.43663	-0.03167	0.10256	1.00000
R5		0.6214	0.7484	0.2978	

Figure 2 – Simple statistics and Spearman Correlation coefficients for the reduced set of financial ratios (SAS output table)

With the remaining ratios we conduct a logistic regression, whose output is listed in the table below. We also include ratio R3 in the analysis, as after comparing the Spearman correlation coefficients of all the ratios, we have observed it yields a good performance.

The LOGISTIC Procedure						Association of Predicted Probabilities and Observed Responses			
Analysis of Maximum Likelihood Estimates									
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Percent Concordant	87.2	Somers' D	0.747
Intercept	1	-5.0036	1.2142	16.9816	<.0001	Percent Discordant	12.5	Gamma	0.749
R1	1	0.0236	0.0138	2.9255	0.0872	Percent Tied	0.2	Tau-a	0.308
R3	1	-0.0474	0.0231	4.2056	0.0403	Pairs	2250	c	0.874
R5	1	0.1074	0.0530	4.1004	0.0429				
R7	1	5.3504	1.4288	14.0219	0.0002				
R8	1	-0.00457	0.00601	0.5779	0.4471				

Figure 3 - Output of the logistic regression (SAS output table)

We can see that the estimated parameter for R8 is not statistically significant: from the last column of the table, the probability to accept the null hypothesis for this estimate is 44.7%, above the threshold of 10% (we consider the significance level of 90% for the null hypothesis tests).

In the second output table, we observe the accuracy ratio for the entities' classification when applying this logistic regression: 87.2% of the cases are correctly classified.

The statistical significant estimates, the ones for the ratios R1, R3, R5, R7 and the intercept are used in computing our own score for each company in the sample. The scores are in the interval [-8,57; 14,8].

By comparing the accuracy ratios obtained for each scoring technique, we conclude that the model we have developed, based on a logistic regression, is the most suitable for the data sample. The results are in line with the findings in the literature: the logistic regression as classification technique outperforms the multiple discriminant analysis and the most suitable technique for creating a rating model is re-estimating the parameters from previous well-known models. This is also true for a central east European emerging economy like Romania and we have proven this statement in the proposed study.

5. Conclusions

With the global financial crisis that began in the USA in 2007 and immediately spread all over the world, many questions arose as to what extent the scoring and bankruptcy models have shown predictive ability in the crisis situation. In the present paper, we have not referred to credit agencies, that apparently played an important role in emphasizing the effects of the crisis, nor have we discussed about the subprime crisis, but we have focused only on the predictive power of statistical models under the global crisis. For this, we have developed three accounting based bankruptcy prediction models and also a cluster analysis of the main financial ratios used in accounting models, with the objective of detecting the financial indicators that “made the difference” in the crisis context.

We conclude that the model we have developed, based on a logistic regression, is the most suitable for the data sample, composed of SMEs accounting ratios from a central-east European emerging economy. Thus, we recommend financial institution to re-estimate the parameters from classical scores and to reconsider the financial ratios, especially in a financial crisis situation.

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